

ESTIMATION OF STAGE DEVELOPMENT
TIME WITH MORTALITY

by

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B.S., National Chung Hsing University, 1980

A MASTER REPORT

Submitted in partial fulfillment of the
requirements for the degree
MASTER OF SCIENCE

Department of Statistics
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1988

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I: INTRODUCTION:

Consider an insect that displays observable stages throughout its lifetime. A common problem is to estimate the average or typical time required for the insect to reach a particular stage (e.g., the mature or adult stage) of development. One approach to this problem is to observe a cohort of such organisms periodically over time and record the number of insects in the various stages and average the times obtained.

It is not always possible to observe a population over time since, in some cases, the insects can not be recaptured to ascertain the difference between previous and current observing time. In other cases the insects may have to be killed or their habitat may have to be destroyed to determine which stage they are in.

We thus take samples from the population of insects at a sequence of times. We let t_1, t_2, \dots, t_F denote the times at which we select a sample. The samples will be taken randomly and without replacement, although we will assume that the population is large enough that the provision for sampling without replacement will not affect calculations and the samples then will be assumed to be independent.

Boyer and Deaton (1984) and Pontius (1987) derived and evaluated nonparametric estimators for the average time of development across various stages, under the assumption of no mortality in the course of the experiment. Here we extend their results to the situation with only one stage, i.e., from non-maturity to maturity, but where the sampled insects might be either dead or alive. In this case, death could occur either before or after maturity. We take independent

samples of fixed size and record the numbers of both mature and non-mature organisms, noting mortality in each group, at various observing times and estimate the average time to maturity, and its corresponding standard error. We compare the mean with its theoretical value and make recommendations for appropriate estimation procedures.

II: THE RELATIONSHIP OF OBSERVATIONS TO THEORETICAL QUANTITIES:

Consider an experiment in which we are interested in progression of an organism from one stage to another stage, i.e., from the stage we label "non-mature" to the stage we label "mature". In the performance of this experiment, we collect independent samples of insects of size n_i at time t_i , $i=1,2,\dots,F$. The insects collected may be either dead or alive, mature or non-mature. We then allocate the elements of the i th sample to one of four categories which are non-mature and dead (ND), non-mature and alive (NA), mature and dead (MD), mature and alive (MA). In each category at time i , the observations have the binomial (n_i, p_{ij}) distribution, $j = \text{ND, NA, MD, MA}$, and the overall data have the multinomial $(n_i, p_{iND}, p_{iNA}, p_{iMD}, p_{iMA})$ distribution.

We let $f(x,y)$ represent the bivariate density of X (time to maturity) and Y (time to death). We presume that $f(x,y) > 0$ only if both x and y are positive. From the figure 2.1, we can see that at time t_i the probabilities for the categories are represented as outlined below.

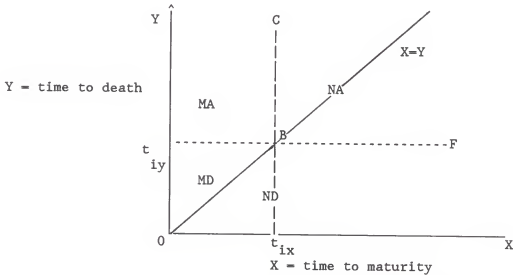
$$\text{ND} = \text{the area of FBOX} , \quad p_{iND} = \int_0^{t_{iy}} \int_y^{\infty} f(x,y) \, dx \, dy,$$

$$\text{NA} = \text{the area of CBF} , \quad p_{iNA} = \int_{t_{iy}}^{\infty} \int_{t_{ix}}^{\infty} f(x,y) \, dx \, dy,$$

$$\text{MD} = \text{the area of B}t_{iy}0 , \quad p_{iMD} = \int_0^{t_{iy}} \int_0^y f(x,y) \, dx \, dy,$$

MA= the area of $Yt_{iy}BC$,

$$p_{iMA} = \int_{t_{iy}}^{\infty} \int_0^{t_{ix}} f(x,y) dx dy.$$



t_{ix} = the shorthand notation for
point $(t_i, 0)$

t_{iy} = the shorthand notation for
point $(0, t_i)$

t_i = time of i th sample

FIGURE 2.1

Note that n_i is the size of the sample taken at the i th sampling time. We let $p_i = p_{iMA} + p_{iMD} = \int_0^{t_{ix}} \int_x^{\infty} f(x,y) dy dx$

Consider an insect that displays observable stages throughout its lifetime. Then, again from figure 2.1, we let

\hat{p}_i = the observed proportion of insects at time i which have
reached the mature stage at time i

$$= \frac{\#MA_i + \#MD_i}{n_i}.$$

Here we let $\#MA_i$ be the number, from the sample of size n_i , found in the MA category, and $\#MD_i$ represents the corresponding number in the MD category at time t_i .

III: THE ESTIMATION PROCEDURE AND THE THEORETICAL CALCULATION:

a: Expected time to maturity

Let X represent time to maturity and let Y represent time to death. Since we are primarily interested in the length of time which it takes to reach maturity, we restrict our attention to those organisms that live long enough to do that. Hence the parameter that we shall estimate is the average time to maturity, among those that do reach maturity. Formally, the parameter of interest is $T = E[X|X < Y]$.

Then, one can show that

$$\begin{aligned}
 f(x|x < y) &= f(x|x-y < 0) \\
 &= \frac{\partial}{\partial x} \frac{P(X \leq x | X-Y < 0)}{P(X-Y < 0)} \\
 &= \frac{\partial}{\partial x} \frac{P(X \leq x \text{ and } X-Y < 0)}{P(X-Y < 0)} \\
 &= \frac{\partial}{\partial x} \frac{\int_{-\infty}^x \int_s^{\infty} f(s, t) dt ds}{\int_{-\infty}^{\infty} \int_s^{\infty} f(s, t) dt ds} \\
 &= \frac{\int_x^{\infty} f(x, t) dt}{\int_{-\infty}^{\infty} \int_s^{\infty} f(s, t) ds dt}
 \end{aligned}$$

Hence

$$\begin{aligned}
 T = E(X|X < Y) &= \int_{-\infty}^{\infty} x f(x|x < y) dx \\
 &= \frac{\int_0^{\infty} \int_x^{\infty} x f(x, y) dy dx}{\int_0^{\infty} \int_x^{\infty} f(x, y) dy dx}
 \end{aligned}$$

equivalently, using change of order of integration,

$$= \frac{\int_0^{\infty} \int_0^y x f(x, y) dx dy}{\int_0^{\infty} \int_0^y f(x, y) dx dy} \quad (3.a.1)$$

Note that we assume the density to be zero when either argument is negative, otherwise the lower limits in the expression above would all be $-\infty$.

b: An estimator of T

In the previous expression for T, let us denote the numerator by U and the denominator by V. Then note that

$$U = \int_0^{\infty} \int_0^y x f(x, y) dx dy = \int_0^{\infty} \int_x^{\infty} x f(x, y) dy dx.$$

If the X-axis is broken into intervals

$[0, t_1], [t_1, t_2], [t_2, t_3], \dots$ then clearly U is reasonably approximated

(in a manner similar to Riemann Sums) by

$$\begin{aligned} \hat{U} = & \hat{p}_1 \left(\frac{t_1}{2} \right) + (\hat{p}_2 - \hat{p}_1) \left(\frac{t_2 + t_1}{2} \right) + (\hat{p}_3 - \hat{p}_2) \left(\frac{t_3 + t_2}{2} \right) + \\ & \dots + (\hat{p}_F - \hat{p}_{F-1}) \left(\frac{t_F + t_{F-1}}{2} \right). \end{aligned}$$

(See Figure 3.1 below, and recognize that \hat{p}_i is the fraction of the sample which lies above the line $X = Y$ and to the left of t_{ix}).

In a similar manner V is just the fraction of the population which lies above the line $X = Y$, and is approximated by \hat{p}_F , the fraction of mature organisms found at the last sampling time. Of course, this presumes that sampling time F is sufficiently large that nearly all organisms that will mature have done so.

Thus we arrive at an estimator \hat{T} by taking $\hat{T} = \hat{U} / \hat{V}$, this gives us

$$\begin{aligned} \hat{T} = & \left[\hat{p}_1 \left(\frac{t_1}{2} \right) + (\hat{p}_2 - \hat{p}_1) \left(\frac{t_2 + t_1}{2} \right) + (\hat{p}_3 - \hat{p}_2) \left(\frac{t_3 + t_2}{2} \right) + \right. \\ & \left. \dots + (\hat{p}_{F-1} - \hat{p}_{F-2}) \left(\frac{t_{F-1} + t_{F-2}}{2} \right) + (\hat{p}_F - \hat{p}_{F-1}) \hat{p}_F \frac{t_F + t_{F-1}}{2} \right] / \hat{p}_F \end{aligned} \quad (3.b.1)$$

and with a little simplification we get an equivalent form which is slightly better for some computations.

$$= - \frac{t_2}{2} \left(\frac{\hat{p}_1}{\hat{p}_F} \right) + \sum_{i=2}^{F-1} \left(\frac{t_{i-1} - t_{i+1}}{2} \right) \left(\frac{\hat{p}_i}{\hat{p}_F} \right) + \left(\frac{t_F + t_{F-1}}{2} \right).$$

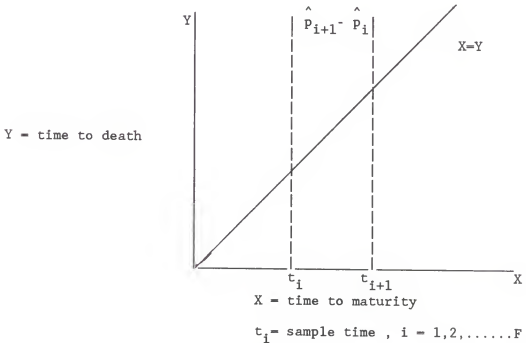


FIGURE 3.1

c: Approximate mean of \hat{T}

Using the approximate formula (Mood, Graybill and Boes, 1974), we find

$$E\left(\frac{A}{B}\right) \approx \frac{\mu_a}{\mu_b} - \frac{1}{\mu_b^2} \text{Cov}(A, B) + \frac{\mu_a}{\mu_b^3} \text{Var}(B).$$

Hence we note that after a little simplification (because $\text{cov}(\hat{p}_i, \hat{p}_F) = 0$)

$$E\left(\frac{\hat{p}_i}{\hat{p}_F}\right) \approx \frac{p_i}{p_F} \left(\frac{n_F p_F^{F+1} - p_F}{n_F p_F} \right) \rightarrow \frac{p_i}{p_F} \quad \text{as } n_F \rightarrow \infty.$$

Therefore $\frac{\hat{p}_i}{\hat{p}_F}$ is an approximately unbiased estimator of the

corresponding ratio of population parameters as $n_F \rightarrow \infty$, and, since \hat{T} is nearly a weighted average of such quantities we are led to believe that \hat{T} will be unbiased or nearly unbiased as an estimator of T .

d: Approximate variance of \hat{T}

Again we use an approximation (Mood, Graybill, and Boes, 1974)

$$\begin{aligned} \text{Var}(\hat{T}) &= \text{Var}\left(\frac{A}{B}\right) \\ &\approx \frac{\mu_A^2}{\mu_B^2} \left[\frac{\text{Var}(A)}{\mu_A^2} + \frac{\text{Var}(B)}{\mu_B^2} - \frac{2\text{Cov}(A, B)}{\mu_A \mu_B} \right] \quad (3.d.1). \end{aligned}$$

In this case

$$A = \hat{U} = \frac{\tau_2}{2} \hat{p}_1 + \sum_{i=2}^{F-2} \left(\frac{\tau_{i-1} - \tau_{i+1}}{2} \right) \hat{p}_i + \left(\frac{\tau_F + \tau_{F-1}}{2} \right) \hat{p}_F,$$

$$B = \hat{V} = \hat{p}_F.$$

$$\text{Thus } \mu_A^2 = \left[\left(\frac{t_2}{2} \right) p_1 + \sum_{i=2}^{F-1} \left(\frac{t_{i-1} - t_{i+1}}{2} \right) p_i + \left(\frac{t_F + t_{F-1}}{2} \right) p_F \right]^2,$$

$$\mu_B^2 = p_F^2,$$

$$\begin{aligned} \text{Var}(A) = & \left(\frac{t_2}{2} \right)^2 \frac{p_1(1-p_1)}{n_1} + \sum_{i=2}^{F-1} \left(\frac{t_{i-1} - t_{i+1}}{2} \right)^2 \frac{p_i(1-p_i)}{n_i} \\ & + \left(\frac{t_F + t_{F-1}}{2} \right)^2 \frac{p_F(1-p_F)}{n_F}, \end{aligned}$$

$$\text{Var}(B) = \frac{p_F(1-p_F)}{n_F},$$

$$\begin{aligned} \text{Cov}(A, B) &= \left(\frac{t_F + t_{F-1}}{2} \right) \text{Var}(\hat{p}_F) \\ &= \left(\frac{t_F + t_{F-1}}{2} \right) \frac{p_F(1-p_F)}{n_F}. \end{aligned}$$

In estimating the variance of \hat{T} , we will insert the corresponding sample quantities (\hat{p}_i 's) into each term and replace in (3.d.1).

e: The comparison to the estimator of Pontius

The \hat{p}_i we have defined represents the proportion of organisms sampled at time i that have reached the mature stage, so that $1 - \hat{p}_i$ (i.e., \hat{q}_i) represents the proportion that have not yet reached the mature stage.

$$\text{Since } \hat{T} = \frac{\left[\frac{t_1}{2} \hat{p}_1 + \sum_{i=2}^F (\hat{p}_i - \hat{p}_{i-1}) \left(\frac{t_i + t_{i-1}}{2} \right) \right]}{\hat{p}_F}$$

$$\text{and } \hat{p}_i = 1 - q_i.$$

$$\text{Then } \hat{T} = \frac{\left[\frac{t_1}{2} + \sum_{i=2}^{F-1} q_i \left(\frac{t_{i+1} - t_{i-1}}{2} \right) - q_F \left(\frac{t_F + t_{F-1}}{2} \right) \right]}{1 - q_F}.$$

Under the assumptions made by Pontius, t_0 must be zero and $\hat{p}_{F,S}$ (our \hat{q}_F) must be zero. Using this condition the expression for \hat{T} reduces to

$$\hat{T} = \frac{t_1}{2} + \sum_{i=2}^{F-1} q_i \left(\frac{t_{i+1} - t_{i-1}}{2} \right).$$

This is exactly the same as the estimator derived by Pontius (1987) for the case in which it is assumed that no insects have died. Hence, although we have extended the method for computations to populations which may contain dead insects, the final result is still the same as the result derived by Pontius if no mortality is observed during the experiment.

IV: NUMERICAL INTEGRATION AND THE SCOPE OF THE SIMULATION STUDY:

a: The numerical integration

Since the quantity $T = E(X|X < Y)$ (which is the parameter of interest in this problem) is not readily derived for the bivariate normal distribution, we used the IMSL subroutine DBLIN to numerically perform the two double integrations required (expression 3.a.1). A copy of the numerical integration program is in the appendix.

b: The scope of the simulation study

We developed a computer program to simulate the experiment described above. As an underlying distribution we used the bivariate normal distribution, which has a large number of shapes depending on one's choices of parameters. Since we wanted to investigate the lifetimes of insects which mature before death, and, since in most populations, lifetime is much longer than maturation time, we chose mean of "time to death" (i.e. μ_y) to be larger than mean of "time to maturity" (i.e. μ_x). For normal distributions, a distance of three standard deviations from the mean in both directions will cover most of the observations. Hence we arbitrarily chose μ_x and μ_y , and then picked standard deviations of "time to death" and "time to maturity" (i.e. σ_y , σ_x , resp.) to be values such that $\mu_x \pm 3\sigma_x$ and/or $\mu_y - 3\sigma_y$ were in between the first and the last observation time. (We were willing to allow some of the insects to die after our experiment was over; that's why we are not concerned with $\mu_y + 3\sigma_y$ being inside our observation time.) We let μ_x be fixed at 6 and σ_x be fixed at 2. We then let $\mu_y = 9$ with $\sigma_y = 2$ and $\sigma_y = 3$, $\mu_y = 12$ with $\sigma_y = 3$ and $\sigma_y = 4$ and

$\mu_y = 15$ with $\sigma_y = 4$ and $\sigma_y = 5$. We also allowed the correlation coefficient ρ to be 0, 0.25 and 0.5. We considered samples of size 15 and 30 at each time period and we had sampling regimens which had 10 sampling times equally spaced (every two time units from time $t = 2$ to time $t = 20$) and unequally spaced (also from $t = 2$ to $t = 20$). For each of the 72 parameter configurations, 100 repetitions of the experiment were run, and computations were made.

For each repetition, \hat{T} and its estimated standard error, which will be denoted by $\text{std}(\hat{T})$, were calculated. Additionally the intervals $\hat{T} \pm 2\text{std}(\hat{T})$ and $\hat{T} \pm 3\text{std}(\hat{T})$ were computed.

For each parameter configuration, several summary statistics over the 100 repetitions were retained and examined. They include:

- (1) Average value of \hat{T} .
- (2) Number of intervals of the form $\hat{T} \pm 2\text{std}(\hat{T})$ that contained T .
- (3) Number of intervals of the form $\hat{T} \pm 3\text{std}(\hat{T})$ that contained T .
- (4) Sample standard deviation of \hat{T} .
- (5) The interval for the mean of \hat{T} , given by average value of $\hat{T} \pm 2 * \text{sample standard deviation of } \hat{T}$.
- (6) Average value of estimated standard error of \hat{T} .

A copy of the simulation program is found in the appendix.

c: Two possible computations:

The population p_i in formula (3.b.1) should be monotonically increasing as a function of i , but when we dealt with the sample proportions, we occasionally found \hat{p}_i to be smaller than \hat{p}_{i-1} . We used both the negative value and zero respectively for the quantity $\hat{p}_i - \hat{p}_{i-1}$ in our simulation study when \hat{p}_i was smaller than \hat{p}_{i-1} .

V: CONCLUSIONS:

We discovered early that the quantity $\hat{p}_i - \hat{p}_{i-1}$ would be negative sometimes, even though the corresponding population quantity is not. We considered replacing these negative values of $\hat{p}_i - \hat{p}_{i-1}$ by zero in the computations. In fact in early stages of the simulation, we did computations both ways. After comparing the results, we recommend the use of the negative value instead of using zero when this occurs. Our recommendation is based on the comparison of the simulation results to the numerical integration results, i.e., the average \hat{T} from 100 simulations with $\hat{p}_i - \hat{p}_{i-1}$ allowed to be negative is considerably closer to the numerical intergration than $\hat{p}_i - \hat{p}_{i-1}$ set to zero. That is, the average \hat{T} from 100 simulations tends to be biased with $\hat{p}_i - \hat{p}_{i-1}$ set to zero.

Using the computer output of the simulation program, we have obtained an estimated value of \hat{T} for each different configuration of $\mu_x, \mu_y, \sigma_x, \sigma_y, \rho$. We have calculated \hat{T} as the average of the estimated \hat{T} 's and formed an interval of the form $\hat{T} \pm 2\hat{\sigma}_T$. Since we have 100 independent \hat{T} 's from 100 independent repetitions, by the Central Limit Theorem \hat{T} will be approximately normally distributed and therefore, the quantity $\hat{T} \pm 2\hat{\sigma}_T$ is approximately a 95% confidence

interval for $E(\hat{T})$. We found that for (1) 29 out of 36 parameter configurations with sample size 15, (2) 26 out of 36 with sample size 30, (3) 27 out of 36 with equally spaced sampling time, (4) 28 out of 36 with unequally spaced sampling times, the confidence intervals contained the parameter of interest (T or $E[X|X<Y]$).

Note that the standard error of \hat{T} is estimated in two ways in this study. The first is from looking at 100 independent repetitions of the experiment and estimating the standard deviation of the population of \hat{T} 's. This quantity is used in the confidence interval calculations described above. The second method is from the series expansion for an individual repetition, and uses formula (3.d.1). We have averaged these values and compared them with the lengths of the confidence intervals described above. (Note that the length of the confidence interval should be $4 \times \hat{\sigma}_T / \sqrt{100}$ or approximately 0.4 times the standard error of \hat{T}). We find good agreement with this criterion in our tables, indicating that the short series expansion gives a good estimate of the actual standard error.

Note also that the standard errors for samples of size 15 are approximately 1.4 (or $\sqrt{2}$) times the corresponding standard errors for samples of size 30. This is an indication to us that even though there is no such term directly found in the Taylor series expansion which gave us (3.d.1), (at least for the situation where all the samples are of the same fixed sample size n), the standard error of the estimator may be proportional to $1/\sqrt{n}$, as are standard errors of means.

Another study that we performed is summarized in table 2. There we used the standard errors for each repetition, using the formula (3.d.1) and denoted here by " $\text{std}(\hat{T})$ ", and formed the intervals $\hat{T} \pm 2\text{std}(\hat{T})$ and $\hat{T} \pm 3\text{std}(\hat{T})$. Then we determined how many of the 100 repetitions generated confidence intervals which contained the parameter values. Although the results do not show perfect agreement with the nominal coverage proportions, they always show around 80 to 95 percent of confidence intervals which contained the parameter values.

As a nonparametric estimator, it was not possible to show that \hat{T} is a Uniform Minimum Variance Unbiased Estimator (UMVUE), but we did demonstrate that it is nearly unbiased for the parameters and distribution used in this study. We also showed that confidence interval coverage is near the nominal levels.

From the simulations we have, we did not find any significant difference in results between 10 equally spaced and unequally spaced observation times. It seems to be a convenience for an experimenter not to have to follow a strict schedule to observe and collect data.

The preceding work is not a complete study of the proposed estimator. Future work could fill several gaps. Foremost among these might be a study using alternative underlying bivariate distributions. (The bivariate normal was used in this case because of ready access to it, the ease of computations, and the versatility in terms of the number of shapes available.) Other aspects which should be investigated include a more thorough study of the effect of sample size, a study of the effects of unequal sample sizes (at the various

observation times), and a more thorough study of the lengths of the intervals between sampling times (how big should they be, and do they need to be equal ?).

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APPENDIX

```

REAL*8 DSEED,UX,UY,VX,VY,PXY,A,B,C,D,DEXP,DSQRT,FD,PP,X,YCD,CN
*,AREA,FN,AY,F,BY
  DIMENSION SIGMA(3),XYMA(200,2),WKVEC(2),KKVEC(2),T(30),MD(30)
*,      MA(30),ND(30),NA(30),P(30),F(30),G(30),GO(30),ET(100)
*,      ETO(100)
  COMMON  UX, UY, VX, VY,PXY
  INTEGER IER
  EXTERNAL FN, FD, AY, BY
C
C *****
C *
C *      T(i) = SAMPLE TIME AT TIME i
C *      i = 1,2,.....10
C *      AX, BX ARE LOWER AND UPPER LIMIT
C *      ON X
C *
C *****
C AX=0.D0
C BX=30.D0
C AERR=0.000001
C
C *****
C *
C *      UNEQUALLY SPACED OBSERVATION TIME
C *      ALTERNATIVELY
C *      SET T(i) = 2 TO 20 BY 2 IS
C *      EQUALLY SPACED OBSERVATION TIME
C *
C *****
C
C T(1)=2.D0
C T(2)=3.D0
C T(3)=6.D0
C T(4)=9.D0
C T(5)=10.D0
C T(6)=11.D0
C T(7)=12.D0
C T(8)=15.D0
C T(9)=16.D0
C T(10)=20.D0
C DSEED      = 466364003.D0
C NR         = 30
C K          = 2
C IR         = 200

```

KKVEC (1) = 1.00
WKVEC (1) = 0.00

```

C
C *****
C *
C *   READ 18 PARAMETER CONFIGURATION
C *
C *****
C

```

```

501 READ(5,105,END=500) UX,UY,VX,VY,PXY
105 FORMAT(5F5.2)

```

```

C
C *****
C *
C *   SET THE FOLLOWING VARIABLES TO BE ZERO
C *   NSAM = # OF SAMPLE SIZE.
C *
C *   SUM = SUM OF  $\hat{T}$ .
C *   SUMV = SUM OF  $\text{STD}(\hat{T})$ .
C *   ETSQ = SUM OF SQUARE OF  $\hat{T}$ .
C *   V = CROSS PRODUCT OF  $\hat{T}$  IN ORDER TO
C *       COMPUTE THE VARIANCE OF  $\hat{T}$ .
C *   ETMIN = MIN OF  $\hat{T}$ .
C *   ETMAX = MAX OF  $\hat{T}$ .
C *   COUNT2 = COUNT THE # OF  $2\text{STD}(\hat{T})$  INTERVALS
C *       THAT CONTAIN THE PARAMETER OF
C *       INTEREST.
C *   COUNT3 = COUNT THE # OF  $3\text{STD}(\hat{T})$  INTERVALS
C *       THAT CONTAIN THE PARAMETER OF
C *       INTEREST.
C *   VV = CROSS PRODUCT OF  $\text{STD}(\hat{T})$  IN ORDER
C *       TO COMPUTE THE VARIANCE OF  $\text{STE}(\hat{T})$ .
C *   THE ABOVE VARIABLES ARE COMPUTED WITH THE
C *   QUANTITY  $\hat{P}_i - \hat{P}_{i-1}$  SET TO NEGATIVE, IN-
C *   STEAD OF THAT SUMO, SUMOV, ETSQO, ETOMIN
C *   ETOMAX, COUNTO2, COUNTO3, VVO, VO ARE
C *   COMPUTED WITH THE QUANTITY  $\hat{P}_i - \hat{P}_{i-1}$  SET
C *   TO ZERO.
C *****
C

```

```

NSAM=0
SUM=0
SUM0=0
SUMV=0
SUMOV=0
ETSQ=0
ETSQ0=0
V=0
V0=0
ETMIN=100.D0
ETMAX=0.D0
ETOMIN=100.D0
ETOMAX=0.D0
COUNT2=0.D0
COUNT3=0.D0
COUN02=0.D0
COUN03=0.D0
SUMV=0.D0
VV=0.D0
VVO=0.D0
CALL ERRSET(208, 256, -1, 1)
C
C *****
C *
C *   DOUBLE INTEGRATION BY USING DBLIN   *
C *   SUBROUTINE.                         *
C *   CN = NUMERATOR.                     *
C *   CD = DENOMINATOR.                   *
C *   AREA = E(X|X<Y).                     *
C *
C *****
C
C   CN = DBLIN(FN, AX, BX, AY, BY, AERR, ERROR, IER)
C   CD = DBLIN(FD, AX, BX, AY, BY, AERR, ERROR, IER)
C   AREA = CN/CD
C   WRITE(6,121)
121  FORMAT('-',14X,'AY',9X,'BY',10X,'AERR',8X,'IER',11X,'CD',11X,'CN'
*    ,10X,'AREA')
C   WRITE(6,122) AX, BX, AERR, IER, CD, CN, AREA
122  FORMAT('-',10X,7(F10.6,2X))
C
C *****
C *
C *   100 REPETITIONS.                     *
C *   SET TT AND VARA = 0.                 *
C *
C *****
C

```



```

DO 6 KK=1,100
TT=0
TTO=0
VARA=0.DO
C *****
C *
C *   GERERATE BIVARIATE NORMAL RANDOM NUMBER *
C *   NR = # OF OBSERVATIONS *
C *   K = # OF RADAM VARIABLE *
C *   SIGMA = VARIANCE-COVARIANCE MATRIX *
C *           (UPPER TRIANGAL) *
C *   IR = # OF ROW DIMENSION *
C *   XYMA = OUTPUT NR BY K MATRIX, *
C *   IER = ERROR PARAMETER (OUTPUT) *
C *
C *****

SIGMA(1)=VX
SIGMA(2)=PXY
SIGMA(3)=VY
IF (KK.GT. 1) GO TO 103
CALL GGNM (DSEED, NR, K, SIGMA, IR, XYMA, WKVEC, IER)
C *****
C *
C *   DETERMINE THE GERERATED DATA THAT *
C *   BELONG TO WHICH OF THE FOUR *
C *   CATEGORIES. *
C *   NA = NON-MATURE AND ALIVE. *
C *   ND = NON-MATURE AND DEAD. *
C *   MA = MATURE AND ALIVE. *
C *   MD = MATURE AND DEAD. *
C *
C *****

NA(1)=0.DO
ND(1)=0.DO
MA(1)=0.DO
MD(1)=0.DO
DO 1 I=1,15
X = UX+ XYMA (I,1)
Y = UY+ XYMA (I,2)
IF (X.LE.T(1) .AND. Y.LE.T(1)) GO TO 5
IF (X.LE.T(1) .AND. Y.GT.T(1)) GO TO 2
IF (X.GT.T(1) .AND. Y.LE.T(1)) GO TO 3
IF (X.GT.T(1) .AND. Y.GT.T(1)) GO TO 4
5 IF (X.GT.Y) GO TO 3
MD(1)=MD(1)+1

```

```

      GO TO 1
2     MA(1)=MA(1)+1
      GO TO 1
3     ND(1)=ND(1)+1
      GO TO 1
4     NA(1)=NA(1)+1
1     CONTINUE
      K=1

C
C *****
C *
C *      CALCULATE Pi, Fi, Gi AND *
C *
C *      F *
C *      TT = Σ Fi * Gi *
C *      i=1 *
C *      (T = TT/PF LABELED BY ET(KK)) *
C *
C *
C *****
C
      P(K)=(MA(K)+MD(K))/15.DO
      IF ((K-1).EQ.0) T(K-1)=0.DO
      F(K)=(T(K)+T(K-1))/2.DO
      IF((K-1).EQ.0) P(K-1)=0.DO
      G(K)=P(K)-P(K-1)
      IF(G(K).LT.0) THEN
        GO(K)=0.DO
      ELSE
        GO(K)=G(K)
      END IF
      TT=TT+F(K)*G(K)
      TT0=TT0+F(K)*GO(K)
      GO TO 109
103  DO 7 LL=1,10
      L=LL
      GO TO 108
109  DO 11 L=2,10
108  CALL GGNSM (DSEED, NR, K, SIGMA, IR, XYMA, KKVEC, IER)
      NA(L)=0.DO
      ND(L)=0.DO
      MA(L)=0.DO
      MD(L)=0.DO
      DO 12 I=1,15
      X = UX + XYMA (I,1)
      Y = UY + XYMA (I,2)
      IF (X.LE.T(L) .AND. Y.LE.T(L)) GO TO 15
      IF (X.LE.T(L) .AND. Y.GT.T(L)) GO TO 25

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```

      IF (X.GT.T(L) .AND. Y.LE.T(L)) GO TO 35
      IF (X.GT.T(L) .AND. Y.GT.T(L)) GO TO 45
15    IF (X.GT.Y) GO TO 35
      MD(L)=MD(L)+1
      GO TO 12
25    MA(L)=MA(L)+1
      GO TO 12
35    ND(L)=ND(L)+1
      GO TO 12
45    NA(L)=NA(L)+1
12    CONTINUE
      P(L)=(MA(L)+MD(L))/15.DO
      IF ((L-1).EQ.0) T(L-1)=0.DO
      F(L)=(T(L)+T(L-1))/2.DO
      IF ( L.EQ.10 ) GO TO 16
      VARA=VARA+(((T(L-1)-T(L+1))/2)**2)*P(L)*(1-P(L))/15.DO
      GO TO 17

C
C *****
C *
C *      CALCULATE VARA, VARB, COVAB, UA, UB *
C *      BY INSERTING SAMPLE QUANTITIES IN *
C *      ORDER TO CALCULATE VAR(T), *
C *      LABELED BY VARET. *
C *
C *****
C
16    VARA=VARA+(((T(L)+T(L-1))/2)**2)*P(L)*(1-P(L))/15.DO
      VARB=P(10)*(1-P(10))/15.DO
      COVAB=((T(L)+T(L-1))/2)*VARB
17    IF((L-1).EQ.0) P(L-1)=0.DO
      G(L)=P(L)-P(L-1)
      IF ( G(L).LT.0) THEN
        GO(L)=0.DO
      ELSE
        GO(L)=G(L)
      END IF
      TT=TT+F(L)*G(L)
      TTO=TTO+F(L)*GO(L)
      IF (LL .GE. 1) GO TO 7
11    CONTINUE
      UA=(TT)**2
      UOA=(TTO)**2
      UB=(P(10))**2
      GO TO 110
7      CONTINUE
      UA=(TT)**2

```

```

      UOA=(TT0)**2
      UB=(P(10))**2
      LL=0
110  NSAM=NSAM+1
      ET(KK) =TT/P(10)
      ET0(KK) =TT0/P(10)
      VARET=(UA/UB)*((VARA/UA)+(VARB/UB)-(COVAB/(UA*UB)))
      VAROET=(UOA/UB)*((VARA/UOA)+(VARB/UB)-(COVAB/(UOA*UB)))
      STDET=SQRT(VARET)
      STDOET=SQRT(VAROET)
      SUMV=SUMV+STDET
      SUMOV=SUMOV+STDOET

C
C *****
C *
C *
C *      CALCULATE 2 & 3STD(T) INTERVALS      *
C *      WITH LABEL DL AND DU AS LOWER        *
C *      AND UPPER LIMIT.                      *
C *
C *****
C
      DL2=ET(KK)-2*STDET
      DU2=ET(KK)+2*STDET
      DL3=ET(KK)-3*STDET
      DU3=ET(KK)+3*STDET
      DOL2=ET0(KK)-2*STDOET
      DOU2=ET0(KK)+2*STDOET
      DOL3=ET0(KK)-3*STDOET
      DOU3=ET0(KK)+3*STDOET
      IF ( AREA.LE.DU2.AND.AREA.GE.DL2) THEN
        COUNT2=COUNT2+1
      ELSE
        COUNT2=COUNT2
      END IF
      IF ( AREA.LE.DU3.AND.AREA.GE.DL3) THEN
        COUNT3=COUNT3+1
      ELSE
        COUNT3=COUNT3
      END IF
      IF ( AREA.LE.DOU2.AND.AREA.GE.DOL2) THEN
        COUNO2=COUNO2+1
      ELSE
        COUNO2=COUNO2
      END IF
      IF ( AREA.LE.DOU3.AND.AREA.GE.DOL3) THEN
        COUNO3=COUNO3+1
      ELSE

```

```

COUN03=COUN03
END IF
SUM=SUM+ET(KK)
SUMO=SUMO+ETO(KK)
ETSQ=ETSQ+ET(KK)*ET(KK)
ETSQ0=ETSQ0+ETO(KK)*ETO(KK)
IF (ET(KK).LT.ETMIN) THEN
  ETMIN=ET(KK)
ELSE
  ETMIN=ETMIN
END IF
IF (ET(KK).GT.ETMAX) THEN
  ETMAX=ET(KK)
ELSE
  ETMAX=ETMAX
END IF
IF (ETO(KK).LT.ETOMIN) THEN
  ETOMIN=ETO(KK)
ELSE
  ETOMIN=ETOMIN
END IF
IF (ETO(KK).GT.ETOMAX) THEN
  ETOMAX=ETO(KK)
ELSE
  ETOMAX=ETOMAX
END IF
IF (NSAM.EQ. 1) GO TO 119
V=V+(NSAM*ET(KK) - SUM)**2/(NSAM*NSAM-NSAM)
VO=VO+(NSAM*ETO(KK) - SUMO)**2/(NSAM*NSAM-NSAM)
VV=VV+((NSAM*STDET - SUMV)**2)/(NSAM*(NSAM-1))
VV0=VV0+((NSAM*STDOET - SUMOV)**2)/(NSAM*(NSAM-1))
GO TO 120
119 V=0.DO
    VO=0.DO
    VV=0.DO
    VV0=0.DO
120 IF (KK.LT.100) GO TO 6
    PER2=COUNT2/100
    PER3=COUNT3/100
    PER02=COUN02/100
    PER03=COUN03/100
    XBAR=SUM/100
    XOBAR=SUMO/100
    STBAR=SUMV/100
    STOBAR=SUMOV/100
    VAR=V/99
    VAR0=VO/99
    VARST=VV/99

```

```

VAROST=VVO/99
STD=SQRT(VAR/100)
STD0=SQRT(VAR0/100)
STDST=SQRT(VARST)
STDOST=SQRT(VAROST)

C
C *****
C *
C *      CALCULATE THE UPPER AND LOWER LIMIT      *
C *
C *      OF THE INTERVAL FORMED  $T \pm 2\sigma^{\wedge}_T$  .      *
C *
C *      T      *
C *
C *****

UPPER=XBAR+2*STD
DLOW=XBAR-2*STD
UPPER0=XBAR+2*STD0
DLOW0=XBAR-2*STD0
WRITE(6,107)
107  FORMAT('1',10X,'UX',10X,'UY',10X,'VX',10X,'VY',10X,'PXY')
C
C *****
C *
C *      WRITE THE PARAMETER CONFIGURATIONS*
C *      AND THE SUMMARY STATISTICS.      *
C *
C *****

WRITE(6,106) UX,UY,VX,VY,PXY
106  FORMAT('-',9X,5(F5.2,7X))
WRITE(6,100)
100  FORMAT('-',10X,'NR', 5X,'K',2X,'SIGMA',18X,'IR')
WRITE(6,101) NR, K, (SIGMA(J),J=1,3), IR
101  FORMAT('-', 8X, I4, 2X, I4, 2X, 3(F5.3,2X), I4/)
WRITE(6,115)
115  FORMAT('-',5X,'THE FOLLOWING VALUE IS WHEN THE PROBABILITY IS NEG
*ATIVE:')
WRITE(6,104) TT, ET(KK), SUM,XBAR,ETSQ,VAR,STD,ETMIN,ETMAX,DLOW,
* UPPER,COUNT2,PER2,COUNT3,PER3,STBAR,VARST,STDST
104  FORMAT('-',10X,'TT=',F10.5,10X,'EXPECTATION OF TIME TO THE MATURI
*TY =', F10.5/10X,'SUM=',F10.5,10X,'XBAR=',F10.5 /10X,'SUM OF SQUAR
*E =',F10.5,/10X,'VARIANCE =',F10.5,10X,'STD =',F10.5/10X,
*'MIN OF ET =',F10.5,10X,'MAX OF ET =',F10.5/10X,'LOWER LIMIT =',
*F10.5,10X,'UPPER LIMIT =',F10.5/10X,'# OF 2STD CONTAIN TRUE VALUE
*=' ,F10.5,10X,'PERCENT OF 2STD CONTAIN TRUE VALUE =',F10.5/10X,
*'# OF 3STD CONTAIN TRUE VALUE =',F10.5,10X,'PERCENT OF 3STD CONTAI
*N TRUE VALUE =',F10.5/10X,'MEAN OF STD OF EXPECTED TIME TO MATURIT

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```

*Y =',F10.5/10X,'VARIANCE OF STD OF EXPECTED TIME TO MATURITY =',
*F10.5,10X,'STD OF STD OF EXPECTED TIME TO MATURITY =',F10.5)
WRITE(6,116)
116 FORMAT('-',5X,'THE FOLLOWING VALUE IS WHEN THE PROBABILITY IS ZER
*0: ')
WRITE(6,117) TT0, ET0(KK), SUM0,X0BAR,ETSQ0,VAR0,STD0,ETOMIN,
* ETOMAX,DLOW0,UPPER0,COUN02,PER02,COUN03,PER03,STOBAR,VAR0ST
*,STD0ST
117 FORMAT('-',10X,'TT=',F10.5,10X,'EXPECTATION OF TIME TO THE MATURI
*TY =', F10.5/10X,'SUM=',F10.5,10X,'XBAR=',F10.5 /10X,'SUM OF SQUAR
*E =',F10.5,/10X,'VARIANCE =',F10.5,10X,'STD =',F10.5/10X,
**'MIN OF ET =',F10.5,10X,'MAX OF ET =',F10.5/10X,'LOWER LIMIT =',
*F10.5,10X,'UPPER LIMIT =',F10.5/10X,'# OF 2STD CONTAIN TRUE VALUE
* =',F10.5,10X,'PERCENT OF 2STD CONTAIN TRUE VALUE =',F10.5/10X
*,'# OF 3STD CONTAIN TRUE VALUE =',F10.5,10X,'PERCENT OF 3STD CONTA
*IN TRUE VALUE =',F10.5/10X,'MEAN OF STD OF EXPECTED TIME TO MATURI
*TY =',F10.5/10X,'VARIANCE OF STD OF EXPECTED TIME TO MATURITY =',
*,F10.5,10X,'STD OF STD OF EXPECTED TIME TO MATURITY =',F10.5)
6 CONTINUE
WKVEC(1)=1.D0
GO TO 501
500 STOP
END

C
C *****
C *
C * DEFINE FN FUNCTION *
C *
C *****
C
FUNCTION FN(X,Y)
IMPLICIT REAL*8 (A-H,O-Z)
COMMON UX, UY, VX, VY, PXY
PP=PX*PXY
A=DSQRT(1-PP)
B=(X-UX)/VX
C=(Y-UY)/VY
D = (B*B) - (2*PXY*B*C) + (C*C)
FN = X * (1/(2*3.14159*VX*VY*A))*DEXP((-1/(2*(1-PP)))*D)
RETURN
END

C
C *****
C *
C * DEFINE FD FUNCTION *
C *
C *****
C

```

```

      FUNCTION FD(X,Y)
      IMPLICIT REAL*8 (A-H,O-Z)
      COMMON UX, UY, VX, VY, PXY
      PP=PX*PXY
      A=DSQRT(1-PP)
      B=(X-UX)/VX
      C=(Y-UY)/VY
      D = (B*B) - (2*PXY*B*C) + (C*C)
      FD = (1/(2*3.14159*VX*VY*A))*DEXP((-1/(2*(1-PP)))*D)
      RETURN
      END

C
C      *****
C      *
C      *      DEFINE LOWER LIMIT      *
C      *      ON Y                      *
C      *
C      *****
C
      FUNCTION AY(X)
      IMPLICIT REAL*8 (A-H,O-Z)
      AY=X
      RETURN
      END

C
C      *****
C      *
C      *      DEFINE UPPER LIMITS      *
C      *      ON Y                      *
C      *
C      *****
C
      FUNCTION BY(X)
      IMPLICIT REAL*8 (A-H,O-Z)
      BY=30.DO
      RETURN
      END

/*
//LKED.SYSLIB DD
// DD
// DD
// DD DSN=SYS1.IMSL.SPFLIB,DISP=SHR
//GO.SYSIN DD *
6 9 2 2 0
6 9 2 2 25
6 9 2 2 50
6 9 2 3 0
6 9 2 3 25

```


6	9	2	3	50
6	12	2	3	0
6	12	2	3	25
6	12	2	3	50
6	12	2	4	0
6	12	2	4	25
6	12	2	4	50
6	15	2	4	0
6	15	2	4	25
6	15	2	4	50
6	15	2	5	0
6	15	2	5	25
6	15	2	5	50

TABLE 1

simulate 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.0$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
true value			5.63			
2	estimated \hat{T}		5.74	5.70	5.77	5.73
	confidence interval of \hat{T}		(5.50, 5.98)	(5.51, 5.90)	(5.53, 6.01)	(5.54, 5.92)
	mean of std(\hat{T})		1.59	1.16	1.53	1.11
	9					
true value			5.62			
3	estimated \hat{T}		5.37	5.62	5.38	5.63
	confidence interval of \hat{T}		(5.06, 5.68)	(5.42, 5.81)	(5.09, 5.68)	(5.44, 5.82)
	mean of std(\hat{T})		1.68	1.19	1.62	1.15

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.0$$

		equally spaced		unequally spaced	
μ_y	σ_y	n = 15	30	15	30
true value		5.89			
3	estimated \hat{T}	5.94	5.95	5.94	5.94
	confidence interval of \hat{T}	(5.83, 6.05)	(5.89, 6.02)	(5.83, 6.05)	(5.88, 6.01)
	mean of std(\hat{T})	0.49	0.34	0.53	0.37
true value		5.85			
4	estimated \hat{T}	6.06	6.05	6.06	6.05
	confidence interval of \hat{T}	(5.97, 6.15)	(5.98, 6.11)	(5.97, 6.16)	(5.98, 6.13)
	mean of std(\hat{T})	0.45	0.34	0.48	0.36

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.0$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
4	true value		5.96			
	estimated \hat{T}		6.02	6.03	6.04	6.05
	confidence interval of \hat{T}		(5.94, 6.09)	(5.97, 6.08)	(5.96, 6.12)	(5.99, 6.11)
	mean of $\text{std}(\hat{T})$		0.38	0.27	0.43	0.31
5	true value		5.93			
	estimated \hat{T}		6.02	6.03	6.01	6.01
	confidence interval of \hat{T}		(5.95, 6.10)	(5.97, 6.08)	(5.92, 6.09)	(5.95, 6.06)
	mean of $\text{std}(\hat{T})$		0.37	0.27	0.42	0.30

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.25$$

		equally spaced		unequally spaced	
μ_y	σ_y	n = 15	30	15	30
2	true value	5.75			
	estimated \hat{T}	5.54	5.65	5.56	5.69
	confidence interval of \hat{T}	(5.29, 5.79)	(5.48, 5.82)	(5.32, 5.79)	(5.53, 5.85)
	mean of $\text{std}(\hat{T})$	1.65	1.20	1.59	1.16
3	true value	5.77			
	estimated \hat{T}	5.55	5.61	5.55	5.64
	confidence interval of \hat{T}	(5.30, 5.80)	(5.41, 5.81)	(5.30, 5.80)	(5.45, 5.82)
	mean of $\text{std}(\hat{T})$	1.58	1.17	1.52	1.12

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.25$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
3		true value	5.96			
		estimated \hat{T}	5.98	5.97	5.99	5.97
		confidence interval of \hat{T}	(5.87, 6.08)	(5.90, 6.04)	(5.89, 6.09)	(5.89, 6.04)
		mean of $\text{std}(\hat{T})$	0.50	0.35	0.53	0.37
4		true value	5.94			
		estimated \hat{T}	5.90	5.93	5.91	5.94
		confidence interval of \hat{T}	(5.80, 6.00)	(5.87, 6.00)	(5.80, 6.01)	(5.87, 6.01)
		mean of $\text{std}(\hat{T})$	0.53	0.36	0.55	0.38

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.25$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
		true value	5.99			
4		estimated \hat{T}	5.94	5.94	5.92	5.95
		confidence interval of \hat{T}	(5.86, 6.02)	(5.88, 5.99)	(5.84, 6.01)	(5.89, 6.00)
		mean of $\text{std}(\hat{T})$	0.37	0.26	0.42	0.30
15		true value	5.98			
5		estimated \hat{T}	6.01	6.01	6.00	6.03
		confidence interval of \hat{T}	(5.93, 6.09)	(5.96, 6.06)	(5.91, 6.08)	(5.97, 6.09)
		mean of $\text{std}(\hat{T})$	0.38	0.27	0.43	0.30

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.5$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
2		true value	5.87			
		estimated \hat{T}	5.81	5.67	5.79	5.66
		confidence interval of \hat{T}	(5.57, 6.06)	(5.49, 5.86)	(5.55, 6.03)	(5.48, 5.83)
		mean of $\text{std}(\hat{T})$	1.46	1.15	1.42	1.10
3		true value	5.92			
		estimated \hat{T}	5.58	5.61	5.56	5.60
		confidence interval of \hat{T}	(5.32, 5.84)	(5.43, 5.80)	(5.30, 5.82)	(5.42, 5.78)
		mean of $\text{std}(\hat{T})$	1.55	1.17	1.50	1.12

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.5$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
<hr/>						
		true value	6.00			
<hr/>						
		estimated \hat{T}	5.82	5.94	5.79	5.94
3		confidence interval of \hat{T}	(5.71, 5.93)	(5.88, 6.01)	(5.67, 5.91)	(5.87, 6.01)
<hr/>						
		mean of std(\hat{T})	0.54	0.36	0.57	0.38
12		true value	6.01			
<hr/>						
		estimated \hat{T}	5.97	5.98	5.96	5.95
4		confidence interval of \hat{T}	(5.88, 6.07)	(5.92, 6.05)	(5.87, 6.06)	(5.87, 6.02)
<hr/>						
		mean of std(\hat{T})	0.46	0.33	0.50	0.35

TABLE 1 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

$$\rho = 0.5$$

		equally spaced		unequally spaced		
μ_y	σ_y	n =	15	30	15	30
true value			6.01			
4	estimated \hat{T}		5.99	6.00	5.96	5.98
	confidence interval of \hat{T}		(5.92, 6.07)	(5.95, 6.05)	(5.88, 6.05)	(5.93, 6.03)
	mean of $\text{std}(\hat{T})$		0.37	0.27	0.42	0.30
true value			6.02			
5	estimated \hat{T}		5.96	6.01	5.95	5.98
	confidence interval of \hat{T}		(5.89, 6.03)	(5.95, 6.07)	(5.87, 6.04)	(5.91, 6.05)
	mean of $\text{std}(\hat{T})$		0.37	0.27	0.42	0.30

TABLE 2

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

μ_y σ_y		ρ		
		0.0	0.25	0.5

	true value	5.63	5.75	5.87
	n = 15	(0.84)	(0.87)	(0.83)
	equally	[0.91]	[0.95]	[0.92]
	spaced 30	(0.89)	(0.95)	(0.93)
		[0.91]	[0.98]	[0.96]
2	-----			
	15	(0.84)	(0.91)	(0.85)
	unequally	[0.94]	[0.96]	[0.93]
	spaced 30	(0.89)	(0.96)	(0.94)
		[0.92]	[0.97]	[0.96]
9	-----			
	true value	5.62	5.77	5.92
	15	(0.88)	(0.86)	(0.93)
	equally	[0.94]	[0.97]	[0.99]
	spaced 30	(0.99)	(0.95)	(0.96)
		[0.99]	[0.96]	[0.97]
3	-----			
	15	(0.91)	(0.90)	(0.97)
	unequally	[0.96]	[0.98]	[0.99]
	spaced 30	(0.98)	(0.95)	(0.96)
		[0.99]	[0.96]	[0.99]

TABLE 2 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

μ_y σ_y		ρ		
		0.0	0.25	0.5
3	true value	5.89	5.96	6.00
	n = 15	(0.89)	(0.91)	(0.97)
	equally	[0.99]	[0.99]	[1.00]
	spaced	(0.94)	(0.94)	(0.98)
	30	[1.00]	[0.99]	[1.00]
	15	(0.92)	(0.93)	(0.96)
	unequally	[1.00]	[0.99]	[1.00]
	spaced	(0.95)	(0.93)	(0.97)
	30	[1.00]	[0.97]	[1.00]
	12			
4	true value	5.85	5.94	6.01
	15	(0.90)	(0.91)	(0.96)
	equally	[0.98]	[0.99]	[1.00]
	spaced	(0.86)	(0.96)	(0.95)
	30	[0.97]	[1.00]	[1.00]
	15	(0.89)	(0.94)	(0.93)
	unequally	[0.97]	[1.00]	[0.98]
	spaced	(0.85)	(0.97)	(0.95)
	30	[0.97]	[1.00]	[0.99]
	4			

TABLE 2 (continued)

simulated 100 times

$$\mu_x = 6, \quad \sigma_x = 2$$

μ_y σ_y		ρ		
		0.0	0.25	0.5
<hr/>				
4	true value	5.96	5.99	6.01
	n = 15	(0.95)	(0.93)	(0.92)
	equally	[1.00]	[1.00]	[1.00]
	spaced	(0.93)	(0.94)	(0.97)
	30	[0.98]	[0.99]	[1.00]
	<hr/>			
	15	(0.93)	(0.93)	(0.94)
	unequally	[1.00]	[0.98]	[0.99]
	spaced	(0.93)	(0.96)	(0.97)
	30	[0.99]	[0.99]	[1.00]
<hr/>				
15	true value	5.93	5.98	6.02
	15	(0.91)	(0.95)	(0.97)
	equally	[1.00]	[1.00]	[1.00]
	spaced	(0.94)	(0.97)	(0.92)
	30	[1.00]	[1.00]	[1.00]
	<hr/>			
	15	(0.91)	(0.94)	(0.92)
	unequally	[0.99]	[0.99]	[1.00]
	spaced	(0.97)	(0.96)	(0.90)
	30	[0.99]	[1.00]	[1.00]

The value in the parenthesis [bracket] is the percent of 2 std C.I.'s
[3 std C.I.'s] which contain the true value.

ESTIMATION OF STAGE DEVELOPMENT
TIME WITH MORTALITY

by
Yeong-Ling Hwang

B.S., National Chung Hsing University, 1980

AN ABSTRACT OF A MASTER'S REPORT

Submitted in partial fulfillment of the
requirements for the degree
MASTER OF SCIENCE

Department of Statistics
KANSAS STATE UNIVERSITY
Manhattan, Kansas

1988

ABSTRACT

Consider an insect that progresses through developmental stages throughout its lifetime. We here consider only one transition, i.e., from non-maturity to maturity. We take independent samples of fixed size and record the numbers of both mature and non-mature organisms, noting mortality in each group, at various observing times. We estimate the average time to maturity, and its corresponding standard error. We also present a simulation study comparing the estimated time to maturity with its theoretical value.